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ABSTRACT

A persistent problem in the evaluation of field-based projects is the lack of no-treatment comparison groups. Frequently, potential comparison groups are confounded by socioeconomic, racial, or other factors. Among the possible methods for dealing with this problem are various matching procedures, but they are cumbersome to use with multiple matching variables. Matching with a large number of variables is possible through the use of cluster analytic techniques. Specifically, principal components analysis followed by the formation of a similarity matrix based on a Euclidean distance metric may be a useful method for identifying potential comparison groups. This technique is illustrated through an example from the evaluation of the PEGASUS-PACE reading management program in the Mobile County (AL) Public School System. (Author/BW)

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SELECTING EVALUATION COMPARISON GROUPS:

A CLUSTER ANALYTIC APPROACH

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Selecting Evaluation Comparison Groups: A Cluster Analytic Approach

A persistent problem in the evaluation of field-based projects is the lack of no-treatment or alternate-treatment comparison groups. Frequently, potential comparison groups are confounded by socioeconomic, racial, or other factors. Numerous methods have been suggested for dealing with this problem. Among these are the use of norming populations as a comparison group, a time series approach, and various matching procedures. The use of a norming population may or may not produce a similar comparison group. Time series designs require data to be collected for several cycles before and after the treatment has been implemented. Aside from methodological problems, matching schemes are cumbersome to use with more than one or two matching variables.

This paper suggests that matching with a large number of varables is possible through the use of cluster analytic techniques. Specifically, it is proposed that principal components analysis followed by the formation of a similarity matrix based on a euclidean distance metric may be a useful method for identifying potential comparison groups.

Method

Prerequisite to application of the procedure is the selection of appropriate matching variables. These variables should be chosen with care and should reflect potential confounding sources of variability between the dependent and independent variables. Possible matching or clustering variables might include race, wealth, or geographic location. The resulting data may be

qualitatively or quantitatively measured. A strong theoretical basis should underpin the selection of this set of variables.

A series of technical problems must also be addressed. The clustering variables must be statistically independent from one another. Variables which are potentially poor choices include ipsative variables and compound indices where all of their component parts are used. Less of a problem may be a ratio and one or both of its parts or any other related index (i.e., sets which share common components). Finally, the user is advised to check the orthogonality of the variable set through the use of principal components analysis. All factors should be associated with eigenvalues which are greater than zero. All variables entered into the principal components analysis should be standardized as z-scores to eliminate the effect of different variances of the cluster variables.

The principal components analysis may shed additional light on the relationships among the variables. If a satisfactory analysis is observed, we may take this as an indication of the validity of the subsequently derived distance matrix. Following the principal components analysis, a similarity matrix may be calculated. We recommend that the similarity measure be based on euclidean distance rather than correlation coefficients when the variables are quantitative. Other similarity measures are available if the data are not measured on a quantitative scale.

Example

The technique suggested in the Method section is illustrated through the use of an example. The procedure described above was applied in the evaluation of the PEGASUS-PACE reading management

program. The target treatment group was the Mobile County Public School System. The matching variables selected for the study were the mean reading achievement statewide assessment scores in grades one through five, per pupil expenditure, white-to-black ratio, teacher-to-pupil ratio, and total student population for each system. All 127 school systems in Alabama were used as potential comparison systems.

A principal components analysis was performed using the 127 school systems in Alabama as the independent variable and the five variables described above as the dependent variables. Table 1 displays the resulting eigenvalues associated with each factor.

Insert Table 1 about here.

All of the eigenvalues were greater than zero. Two of the factors accounted for approximately 52% of the observed variance. These two factors (not rotated) and their associated loadings are presented in Table 2.

Insert Table 2 about here.

Table 2 suggests that Factor 1 is influenced primarily by the variables, per pupil expenditure, teacher-to-pupil ratio, and achievement. Factor 2 is influenced primarily by system size and race ratio. An examination of Figure 1 indicates that most of the variability of the systems is accounted for by Factor 1, however, Factor 2 does separate the predominantly smaller and white systems from the larger and predominantly black systems (vertical axis).

Insert Figure 1 about here.

To illustrate the importance of the initial selection of variables, a second principal components analysis was performed on a variable set without the size variable. As before a two factor solution was extracted, however, only the variable white-to-black ratio loaded on the second factor. Figure 2 presents graphically the results of this analysis.

Insert Figure 2 about here.

It is interesting to note the extreme compression of the systems along the Y-axis and most important, the disappearance of the "big system" cluster. In this analysis the Mobile system (the state's largest) has loaded with the broadly undifferentiated mass of moderately achieving, paying, and size systems.

A matrix of euclidean distances was calculated among the 127 Alabama systems. Raw data were standardized prior to the formation of the distance matrix. Two separate analyses were run. Table 3 presents the results of the analyses.

Insert Table 3 about here.

The four systems closest to Mobile are represented for both analyses. The first analysis, which included a size variable, identified the Birmingham, Huntsville, Jefferson County, and Montgomery school systems as the best matches for Mobile. These

are four of the largest school systems in the state. The second analysis, which held out the size variable, grouped four rural and small systems with Mobile. Thus, with the size of the system included in the analysis, Mobile's best match is Jefferson County, the state's second largest system. With size held out of the analysis, Mobile's closest match is Calhoun County, a rather small rural system.

Summary

The use of any multivariate procedure involves the user in an intensely creative and interactive process. Alternative conceptualizations must be examined and alternative hypotheses considered.

We believe that the analysis presented in this paper can serve three functions. First, a very practical problem may be addressed directly, that is, the selection of comparison groups for evaluation purposes. Second, this process may provide us with new information which is related to educational outcomes. Finally, multivariate procedures may be utilized in an a priori fashion to select "demonstration" systems for model programs. In this way we may begin to develop a system for matching specific instructional programs with educational units most likely to benefit from such programs.

We also believe that this process for selecting comparison groups has several advantages over other approaches. First, the number of clustering variables is not limited as it would be if hand matching were done. Second, the procedure makes no a priori assumptions regarding the relationship among the comparison units.

The third advantage is that the user is able to identify several possible comparison groups.

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Eigenvalue Inspection

Factor	Variance Explained	Cum Variance
1	1.492	.290
2	1.085	.515
3	.943	.704
4	.655	.875
5	.621	1.000

Table 1

Unrotated Factor Loadings (pattern)

Variable	Factor 1	Factor 2
acheve	.602	.342
totkids	.341	-.603
$ratio	.747	-.192
w/b	.222	.751
kid/tch	.635	-.071

Table 2

The Effect of Variable Selection on the Distance Matrix

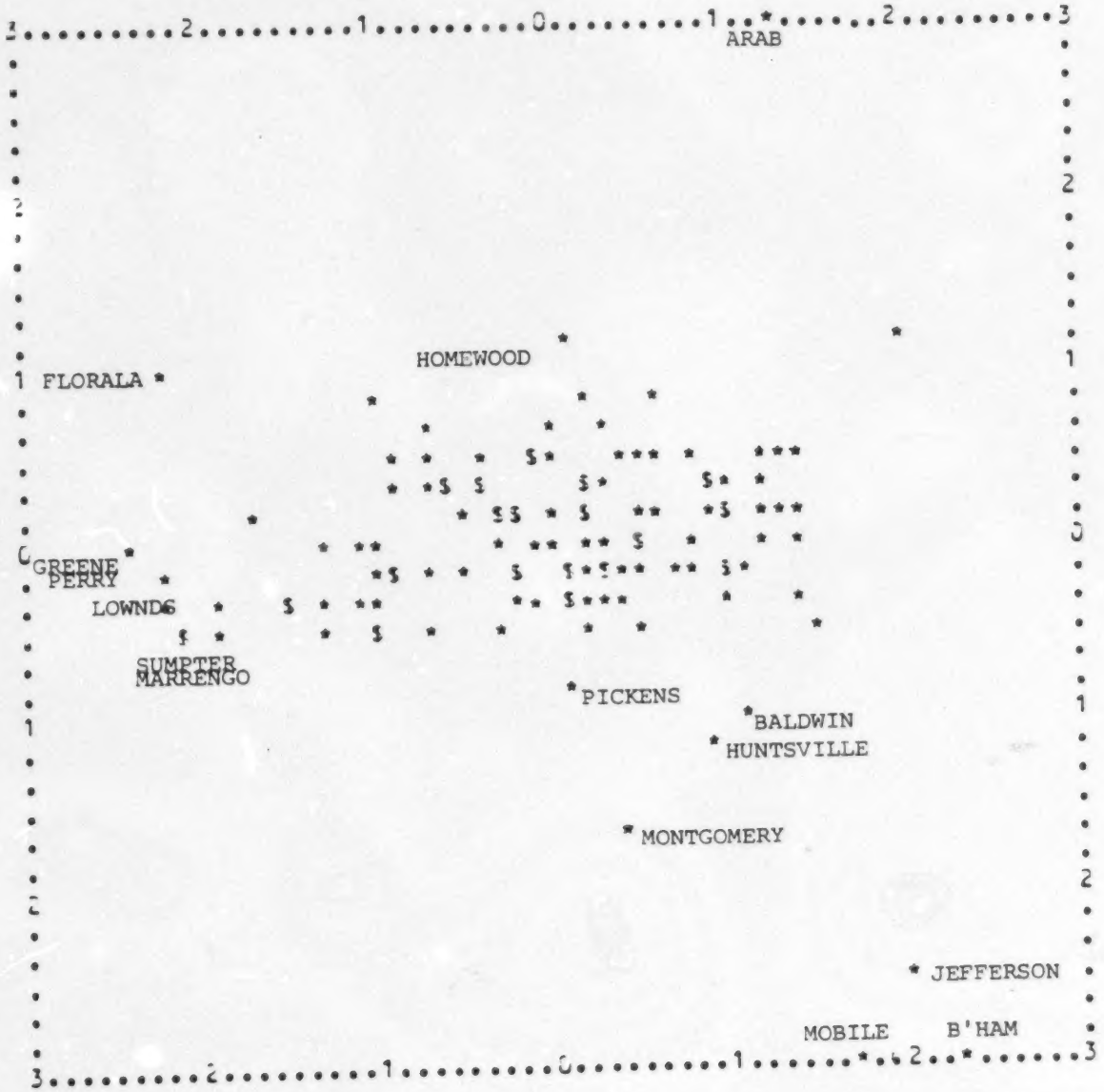
Vars	Dist from Mobile	System Name
tot,w/b	4.96	Birmingham
$,achieve	3.97	Huntsville
kid/teach	1.91	Jefferson
	3.35	Montgomery
w/b, $	.40	Calhoun
achieve	.5000	Guntersville
kid/teach	.4556	Houston
	.54	Lanetta

Table 3

PCA ANALYSIS FOR EIGENVALUE CHECK

FACTOR SCORES

X-AXIS IS FACTOR 1, Y-AXIS IS FACTOR 2



OVERLAP IS INDICATED BY A DOLLAR SIGN. SCALE IS FROM -3 TO +3.
FACTOR SCORES GREATER THAN 3 ARE PLOTTED AS 3.
FACTOR SCORES LESS THAN -3 ARE PLOTTED AS -3.

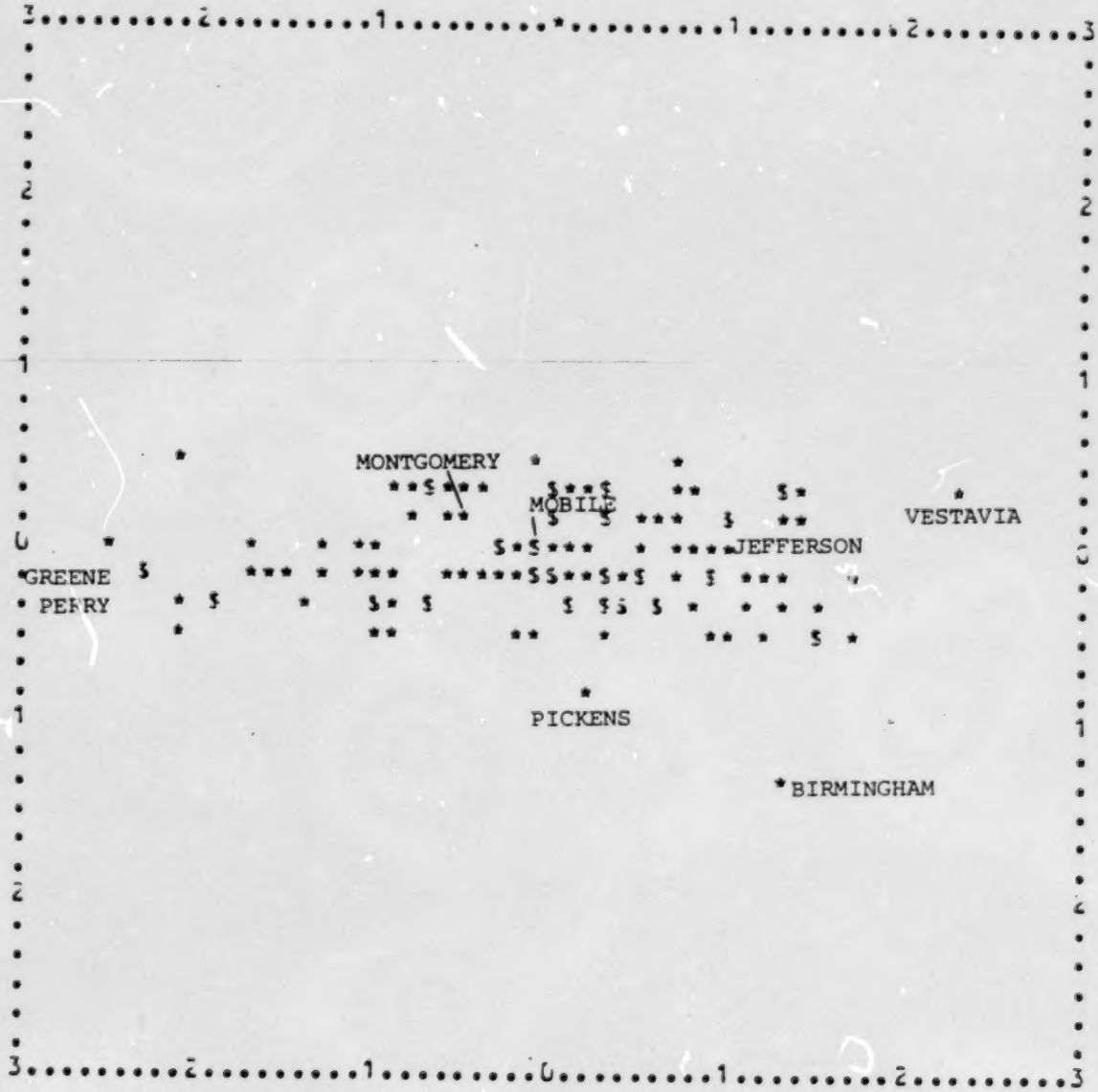
CPU TIME USED 20.573 SECONDS

Figure 1

PCA ANALYSIS FOR EIGENVALUE CHECK

FACTOR SCORES

X-AXIS IS FACTOR 1, Y-AXIS IS FACTOR 2



OVERLAP IS INDICATED BY A DOLLAR SIGN. SCALE IS FROM -3 TO +3.
FACTOR SCORES GREATER THAN 3 ARE PLOTTED AS 3.
FACTOR SCORES LESS THAN -3 ARE PLOTTED AS -3.

CPU TIME USED 16.850 SECONDS

Figure 2